Local Ensemble Transform Kalman Filter Assimilation of Precipitation with the NCEP Global Forecasting System

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Introduction

- Many in-situ and satellite based precipitation observations have been made available, but the assimilation of precipitation is still difficult because of :
  - Nonlinear observation operator
  - non-Gaussianity of the precipitation variable
  - imperfect precipitation parameterization in the numerical model
  - unknown errors associated with the precipitation observations.
- It is relatively easy to force the model precipitation to be close to the observed values; however, since this is not an efficient way to modify the potential vorticity field that the model woud remember, model forecasts tend to lose their additional skill after few forecast hours.
- Proposed method of precipitation assimilation:
  - Local ensemble transform Kalman filter (LETKF)
  - Cumulative distribution function (CDF)-based transformation applied to the precipitation variable (instead of logarithm transformation).
  - Ensemble background-based observation selection criterion (instead of observation-based criterion).

CDF-based Gaussian transformation

- The "Gaussian anamorphosis" (also used by Schöniger et al. 2012 in hydrology):

$$y_{trans} = G^{-1}[F(y)]$$

y : Original variable.

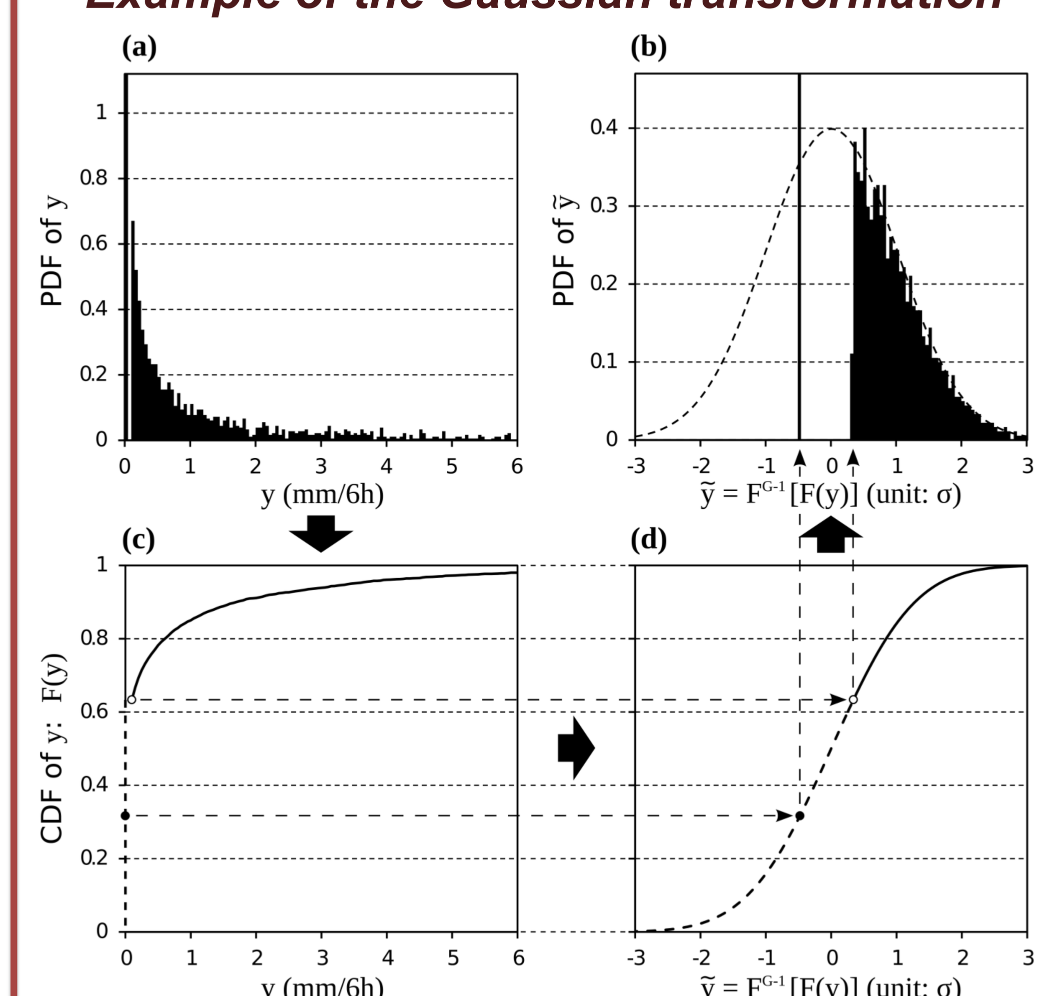
F : Empirical cumulative distribution function (CDF) of y based on a long period of observations or model climatology.

G^{-1} : Inverse CDF of normal distribution.

$$G^{-1}(x) = \sqrt{2}erf^{-1}(2x-1)$$

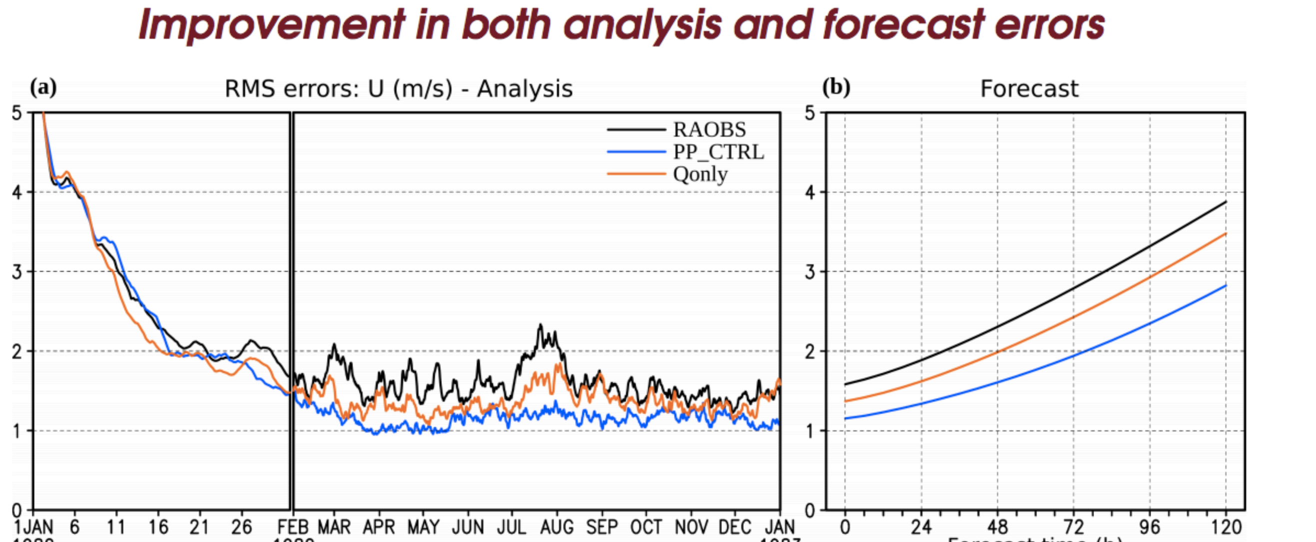
- Precipitation variables contain a large portion of zero values.
  - Zero precipitation values have to be considered in the transformation.
  - A nature choice: assigning the middle value of zero-precipitation cumulative probability to *F(0)*.
- LETKF assimilation of precipitation is performed on the transformed space.
- The transformation can apply to observed values and model background values separately. In this case, it not only transforms an arbitrary variable into a Gaussian variable, but also functions as a "CDF-based bias correction"

Example of the Gaussian transformation



Perfect model experiment with SPEEDY model

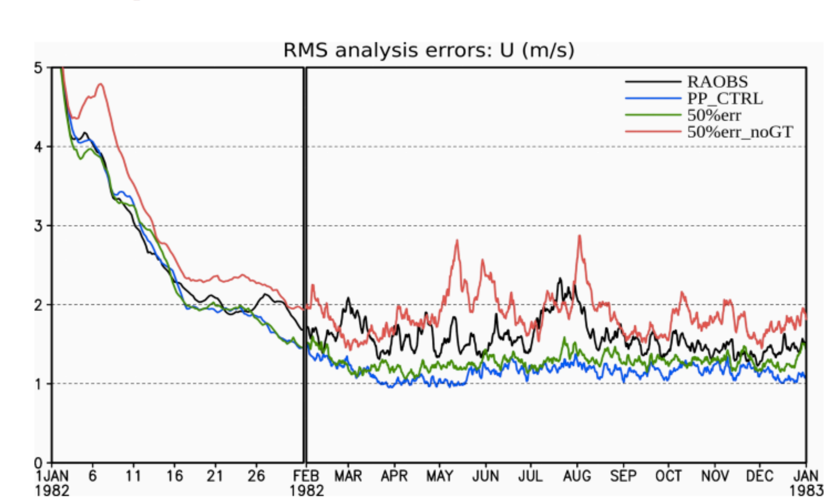
Improvement in both analysis and forecast errors



(Spin-up) (After the spin-up) (11-month average after the spin-up period)

- **RAOBS**: Assimilate rawinsonde observations
- **PP_CTRL**: Assimilate rawinsonde observations + uniformly distributed global precipitation
- **Qonly**: Same as PP_CTRL, but only update moisture field by precipitation assimilation

Impact of Gaussian transformation

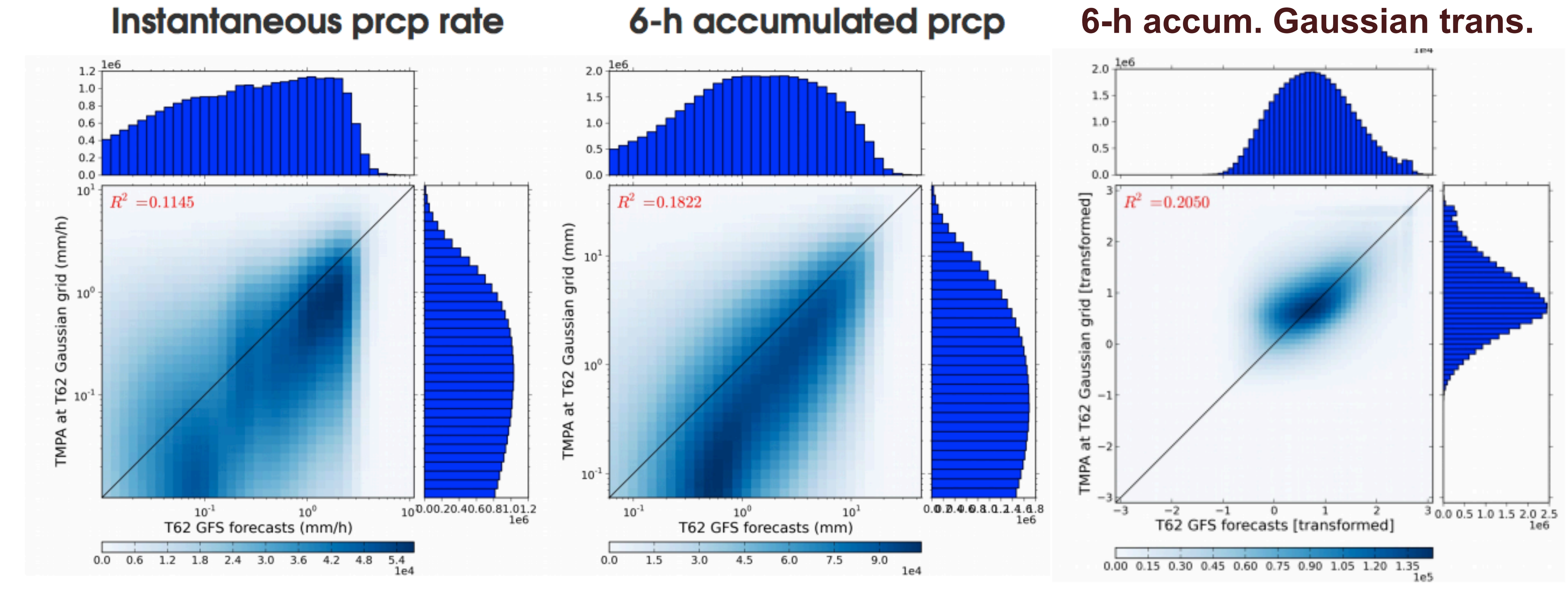


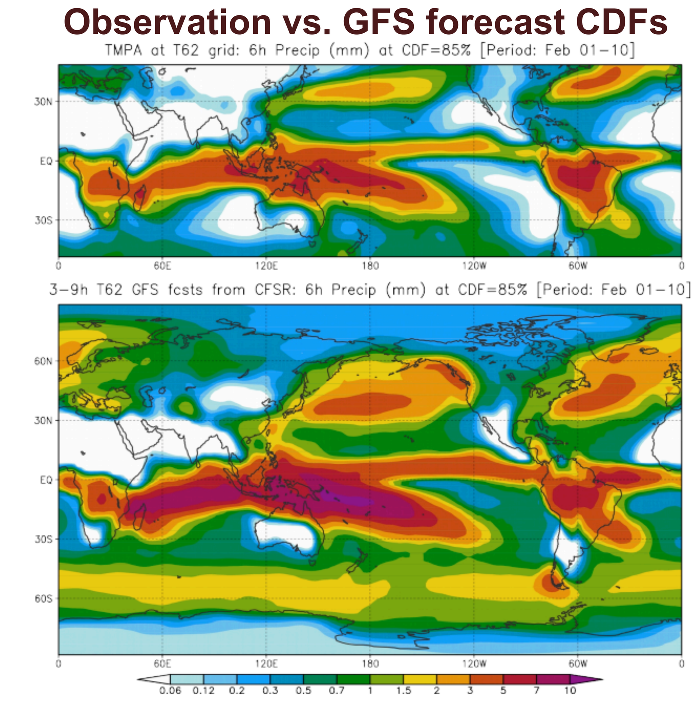
- **50%err**: Same as PP_CTRL, but increase the observation error of precipitation observations from 20% to 50%.
- **50%err_noGT**: Same as 50%err, but do not use the Gaussian transformation

The analysis and 5-day forecasts both show improvements in idealized experiments.

Statistics with TMPA and GFS 3-9 hour forecasts

- We target to run assimilation experiments at a T62 resolution. TMPA data are upscaled to the Gaussian grid used by the T62 GFS model using an areal conservative remapping.
- 2001-2010 (10 year) period is chosen to compute all these statistics.
- 9-hour GFS model forecasts initialized from every 6-hour NCEP Climate Forecast System Reanalysis (CFSR) are conducted within the 10-year period, in which the 3-9 hour forecasts (i.e., assimilation window) are compared to the TMPA data. In the LETKF data assimilation, this period of model forecasts is used as background.

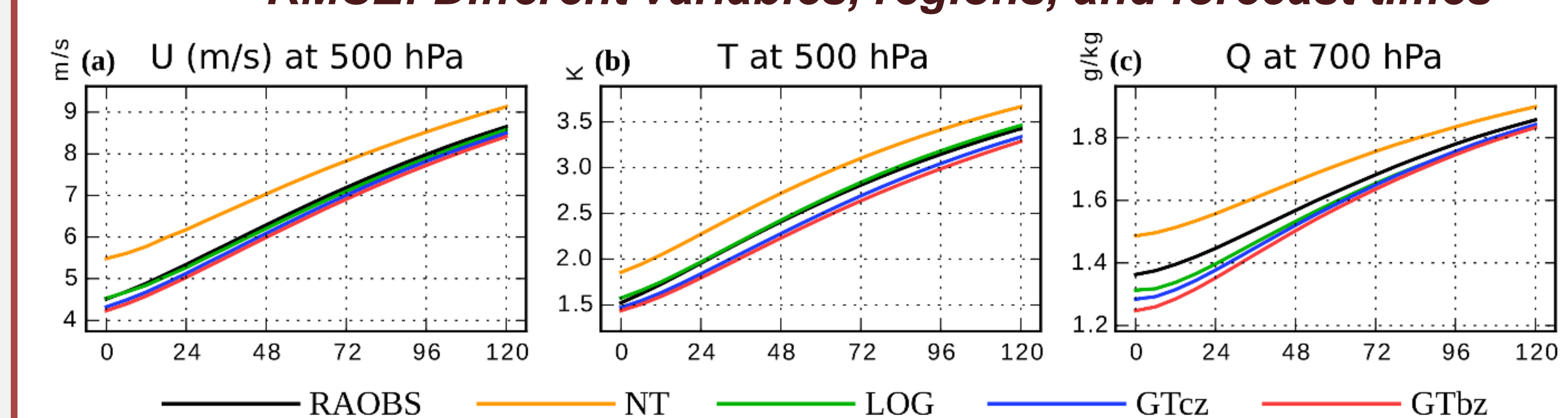


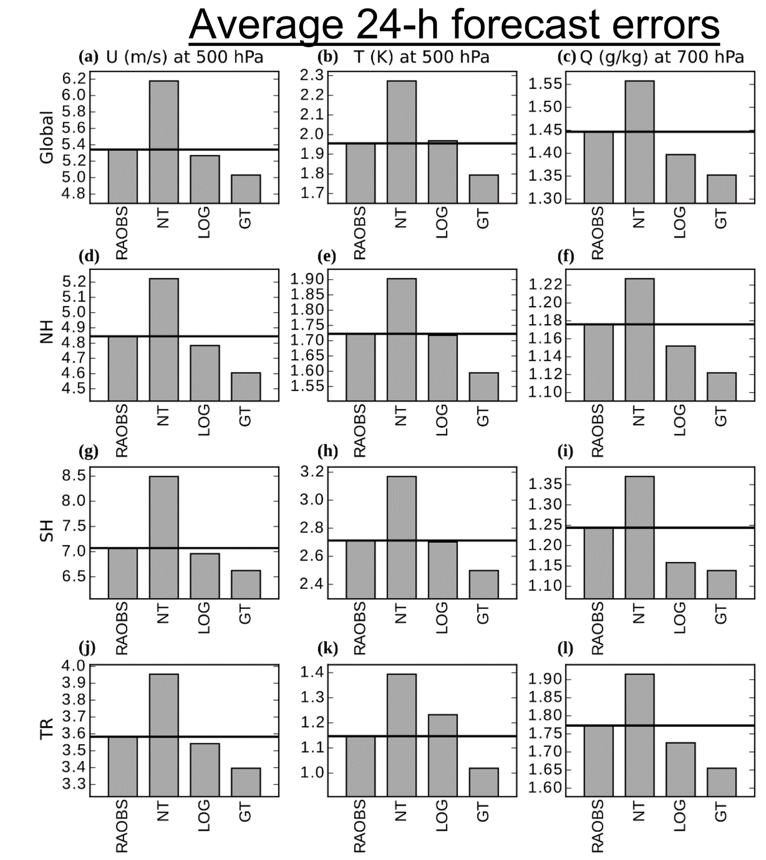


CDFs of both TMPA and GFS forecasts

- Empirical CDFs as a function of geographic location and 10-day period of the year (i.e., 1-10 Jan., 11-20 Jan., … etc.) are constructed from the 10-year TMPA data and GFS forecasts, in order to define the Gaussian transformation of the precipitation variables for both observations and model background.
- When computing the CDF at each grid point and each 10-day period, all data within 500-km radius and +/- 20-day period are considered in order to obtain spatially and temporally smooth CDFs.

RMSE: Different variables, regions, and forecast times





All variables in all regions are improved in real data/model experiments.

Conclusions and Future directions

- Assimilating precipitation with LETKF, which does not require linearization of the model, and gives us the "error correlation of the day", can improve all "master" variables more efficiently comparing to nudging or variational approaches, and thus lead to improvement in longer-term model forecasts.
- Using Gaussian transformation for precipitation based on its climatological distribution in the model and observations, and also quality control criteria specialized for precipitation, we improve not only SPEEDY, but also GFS model analysis and 5-day forecasts.
- The effect of precipitation assimilation improves all variables in all regions.

- We would like to extend the method on tropical cyclone precipitation assimilation in Weather Research & Forecasting Model. Since tropical cyclones are a strongly dynamic-thermodynamic coupling system, improving potential vorticity with precipitation assimilation may have great impact. Taking advantages of TRMM, GPM data and this effective method of precipitation assimilation, it may be possible to improve eyewall and rainband structures and thus produce better intensity forecasts.
- We are exploring several other advances and plan to have a system tested and ready for operational implementation.